RadLoco: A Rapid and Low Cost Indoor Location-Sensing System

Eugene Hyun, Michael McGuire, Mihai Sima

Department of Electrical and Computer Engineering
University of Victoria

Chinacom 2008 Conference

Outline

Location Aware Computing

Motivation

Location aware computing consists of the use of location information to improve the value of a wireless network for the users

Examples

- providing **navigation** through unfamiliar environments
- dynamic **pre-allocation** of resources

Location Aware Computing

Motivation

Location aware computing consists of the use of location information to improve the value of a wireless network for the users

Examples

- providing **navigation** through unfamiliar environments
- dynamic **pre-allocation** of resources

Location Aware Computing

Motivation

Location aware computing consists of the use of location information to improve the value of a wireless network for the users

Examples

- providing **navigation** through unfamiliar environments
- dynamic **pre-allocation** of resources

Current Technologies for Location-Sensing

Global Position System (GPS) and Cellular Networks

- poor location performance indoors

Wireless Local Area Networks

- Many environments have ubiquitous wireless networks
- Wireless network access is being incorporated into smaller mobile devices

Current Technologies for Location-Sensing

Global Position System (GPS) and Cellular Networks

- poor location performance indoors

Wireless Local Area Networks

- Many environments have **ubiquitous** wireless networks
- Wireless network access is being incorporated into smaller mobile devices

Current Technologies for Location-Sensing

Global Position System (GPS) and Cellular Networks

- poor location performance indoors

Wireless Local Area Networks

- Many environments have **ubiquitous** wireless networks
- Wireless network access is being incorporated into smaller mobile devices

Problem Definition

Problem

- The relationship between location and radio signal strength is highly **non-linear** and not known a priori.
- Survey data collection is **time consuming**.

Solution

- Use non-parametric **estimation technique** to reduce noise and required number of survey points.
- **Sensory network** of Ultrasonic/Radio devices to aid in rapid survey data collection.

Problem Definition

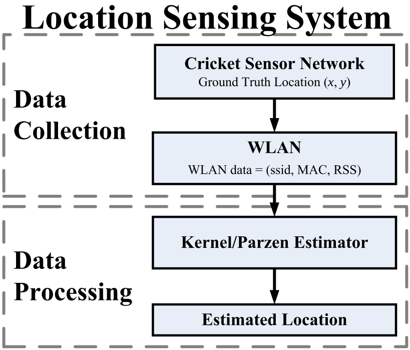
Problem

- The relationship between location and radio signal strength is highly **non-linear** and not known a priori.
- Survey data collection is **time consuming**.

Solution

- Use non-parametric **estimation technique** to reduce noise and required number of survey points.
- **Sensory network** of Ultrasonic/Radio devices to aid in rapid survey data collection.

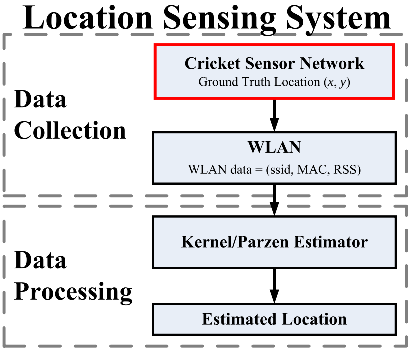
Location Sensing System Overview



Details

2 stages: Data Collection and Data Processing

Location Sensing System Overview



Details

Data Collection: Cricket Sensory Network

Cricket Sensory Network for Ground Truth Location

Sensory Network

- provide **ground truth location** for survey point.
- use **modified steepest descent** and Newton's method optimization

Cricket Details

- **accuracy** = mean accuracy of 14 cm
- **sensors** = ultrasonic (40 kHz), radio (433 MHz)
- **developers** = Networks and Mobile Systems Group at MIT.
- **cost** = $3000 for 12 crickets covering 500 m^2

Cricket Sensory Network for Ground Truth Location

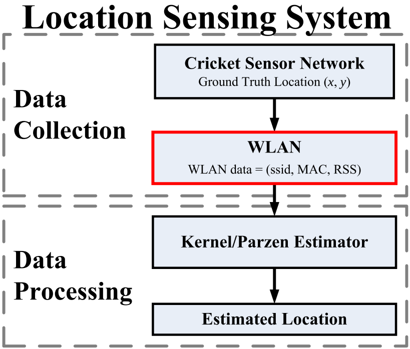
Sensory Network

- provide **ground truth location** for survey point.
- use **modified steepest descent** and Newton's method optimization

Cricket Details

- **accuracy** = mean accuracy of 14 cm
- **sensors** = ultrasonic (40 kHz), radio (433 MHz)
- **developers** = Networks and Mobile Systems Group at MIT.
- **cost** = \$3000 for 12 crickets covering 500 m^2

Location Sensing System Overview



Details

Data Collection: WLAN

WLAN information

WLAN data

- **RSS** from base station
- **MAC** of base station
- Time
- SSID (network ID)

Survey Data

- WLAN data and ground truth location compose of a **survey point**.
- Collect several survey points within a floor or room to create a **survey data set**.

WLAN information

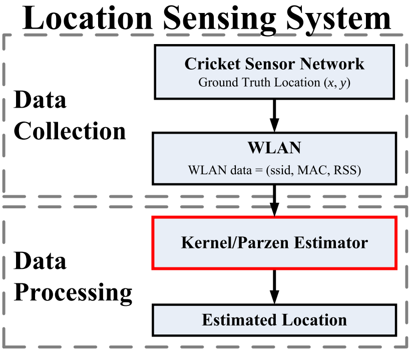
WLAN data

- **RSS** from base station
- **MAC** of base station
- Time
- SSID (network ID)

Survey Data

- WLAN data and ground truth location compose of a **survey point**.
- Collect several survey points within a floor or room to create a **survey data set**.

Location Sensing System Overview



Details

Data Processing: Location Estimation

Location Estimation

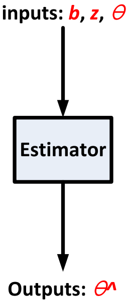
Estimation Algorithm

Non-Parametric **Kernel/Parzen Estimation** Technique using a sum of multivariate Gaussian Distributions.

Variables

- $\boldsymbol{b}$ = vector of base stations (WLAN)
- $\boldsymbol{z}$ = vector of receive signal strength measurements (WLAN)
- θ = x & y coordinates (survey points)
- $\hat{\theta}$ = x & y coordinate (estimated location)

Location Estimation



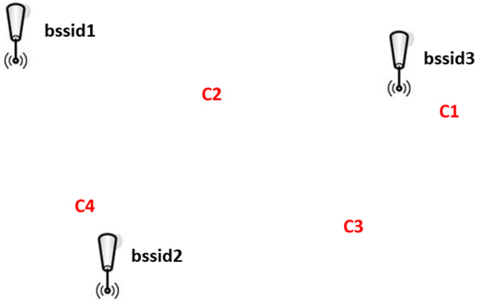
Estimation Algorithm

Non-Parametric **Kernel/Parzen Estimation** Technique using a sum of multivariate Gaussian Distributions.

Variables

- $\mathbf{b}$ = vector of base stations (WLAN)
- $\mathbf{z}$ = vector of receive signal strength measurements (WLAN)
- θ = x & y coordinates (survey points)
- $\hat{\theta}$ = x & y coordinate (estimated location)

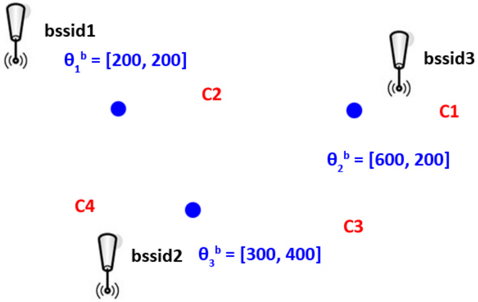
Simple Graphical Example



Explanation

3 base stations and 4 cricket sensors

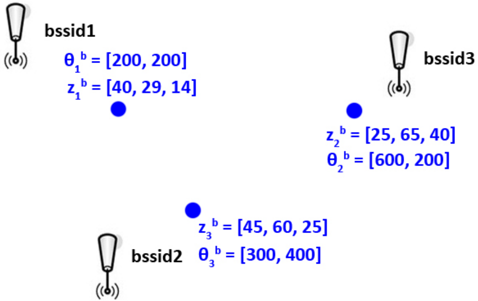
Simple Graphical Example



Explanation

crickets provide ground truth location (blue dots)

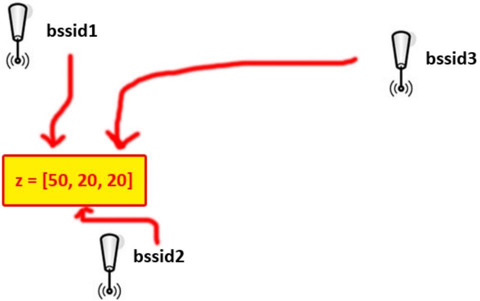
Simple Graphical Example



Explanation

base stations provide RSS vector (z)

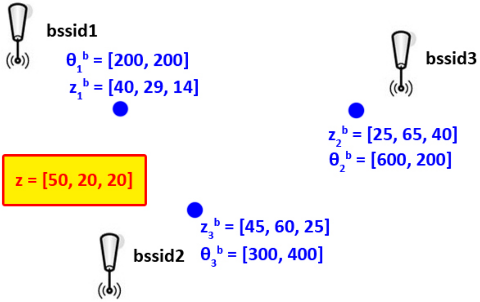
Simple Graphical Example



Explanation

take RSS measurement at current unknown location

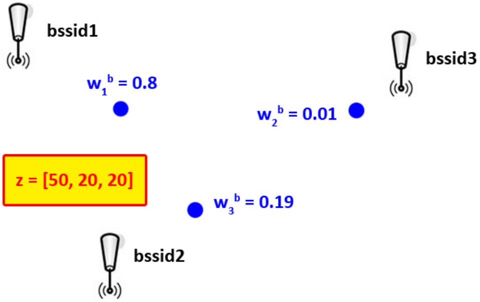
Simple Graphical Example



Explanation

and use the survey points collected prior

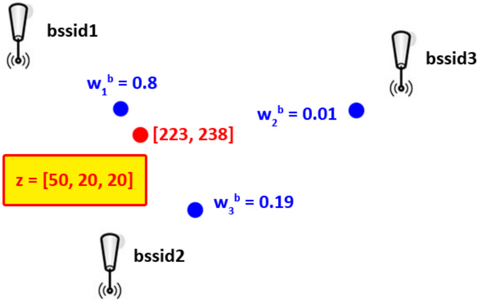
Simple Graphical Example



Explanation

to calculate the weight from **z** feature and Kernel estimator

Simple Graphical Example



Explanation

estimated location is calculated using weights and θ feature

ECS 116 - Experimental Setup

Environment

- Engineering and Computer Science building lecture hall 116
- 117 seats divided into 8 rows
- 10 x 13 meters with 2 seats/m

Equipment

- hardware: Dell Inspiron laptop + Intel 802.11g WLAN card
- software: Netstumber, **Radloco**, MySQL

ECS 116 - Experimental Setup

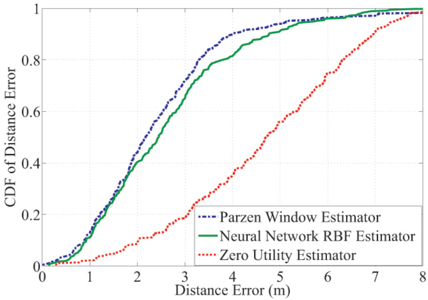
Environment

- Engineering and Computer Science building lecture hall 116
- 117 seats divided into 8 rows
- 10 x 13 meters with 2 seats/m

Equipment

- hardware: Dell Inspiron laptop + Intel 802.11g WLAN card
- software: Netstumber, **Radloco**, MySQL

ECS 116 - Experimental Results



Description

- We were able to obtain over 80% accuracy within 4 meters or 6 seats.
- Motivation for ECS 5th and 6th floor

ECS 5th and 6th floors - Experimental Setup

Environment

- Building has an **atrium** like structure
- Experiments were restricted to **hallways** and public conference rooms.

Base Station (WAP) Information

- WAPs from networks **UVicOpen** or **engrnet**.
- more than 35 unique WAPs and minimum of 12 WAPs visible at any location on a floor.

ECS 5th and 6th floors - Experimental Setup

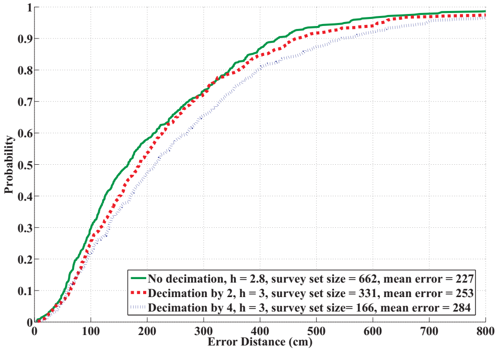
Environment

- Building has an **atrium** like structure
- Experiments were restricted to **hallways** and public conference rooms.

Base Station (WAP) Information

- WAPs from networks **UVicOpen** or **engrnet**.
- more than 35 unique WAPs and minimum of 12 WAPs visible at any location on a floor.

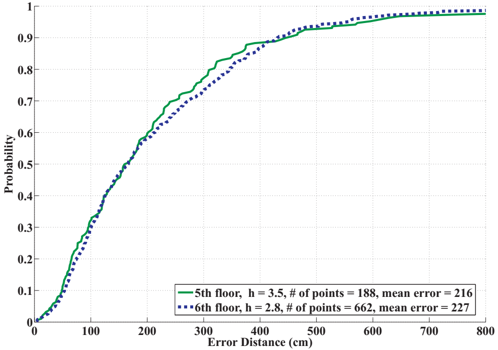
Experimental Results - Decimation of Survey Set



Description

Decimating survey set yields near identical performance.

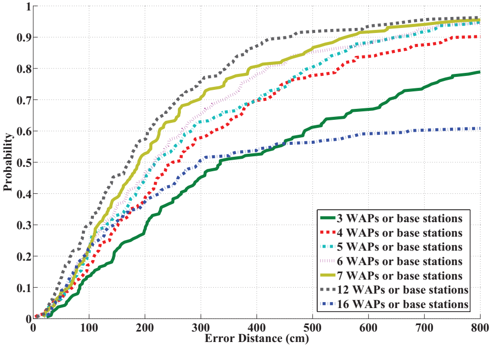
Experimental Results - 6th vs. 5th floor



Description

Both floor have similar accuracy of **3.5 m** more than 80% of the time.

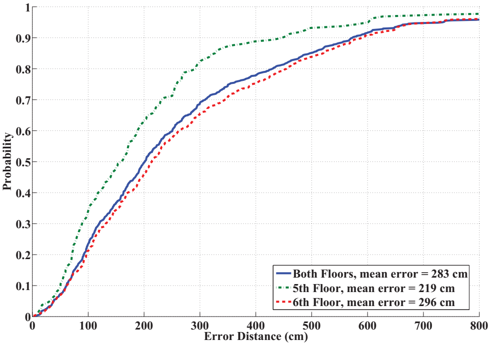
Experimental Results - Number of Base Stations



Description

Increasing base stations yields better accuracy

Experimental Results - Combined Datasets



Description

Combined floors data sets provides 3D location accuracy with over **98% floor accuracy**

Conclusions

Major Contributions

- location-sensing system that locates mobile computing devices indoors based on **WLAN** technology.
- **sensory network** composed of radio/ultrasonic devices allow rapid data collection
- **98% accuracy** floor accuracy and location estimations within **3.5m** of true location

Conclusions

Further Research

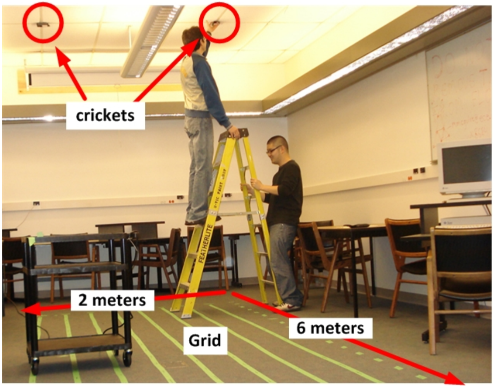
- IEEE 802.16, **WiMAX**, can be extended for indoor location.
- sensory network **calibration** on walls
- **real-time** location estimation for the RadLoco software

Conclusions

List of Publications

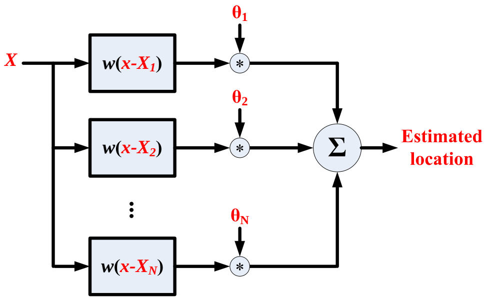
1. **Eugene Hyun**, Michael McGuire, Mihai Sima, "RadLoco: A Rapid and Low Cost Indoor Location-Sensing System" IEEE 3rd International Conference on Communications and Networking in China, Hangzhou, Aug 2008.
2. Michael McGuire, **Eugene Hyun**, Mihai Sima, "Location Aware Computing for Academic Environments" The 3rd International Conference on Quality of Service in Heterogeneous Wired/Wireless Networks (MobConQoE '07), Vancouver, Canada, Aug 2007.
3. **Eugene Hyun**, Diego Felix, Michael McGuire, Mihai Sima, "A Three-Dimensional Indoor Location-Sensing using Radio and Ultrasonic Sensing Technologies", ETRI Journal (in Preparation)
4. **Eugene Hyun**, Mihai Sima, Michael McGuire, "Reconfigurable Implementation of Wavelet Transform on an FPGA-Augmented NIOS Processor", IEEE Canadian Conference on Electrical and Computer Engineering (CCECE '06), Ottawa, Canada. May 2006, pp. 1052-1055.

Thank you!



Thank you!

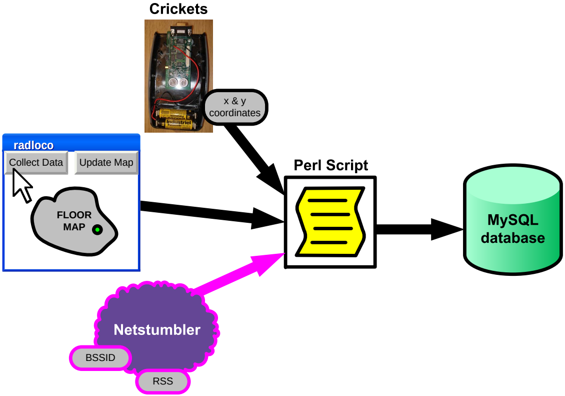
Block Diagram of Estimated Location



weighted average function

$$w_i = \frac{\mathrm{K}(\boldsymbol{x} - \boldsymbol{X}_i)}{\sum_{i=1}^{N} \mathrm{K}(\boldsymbol{x} - \boldsymbol{X}_i)} \quad (1)$$

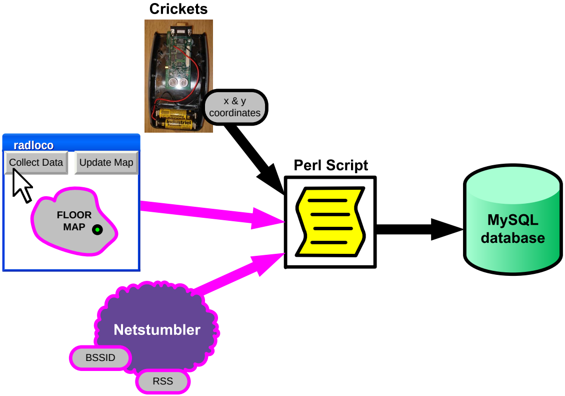
Software Setup



steps

start Netstumbler and load Radloco perlscript

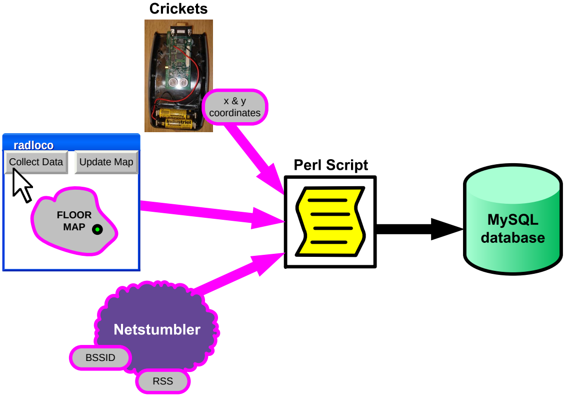
Software Setup



steps

load map into Radloco and click on map to record data

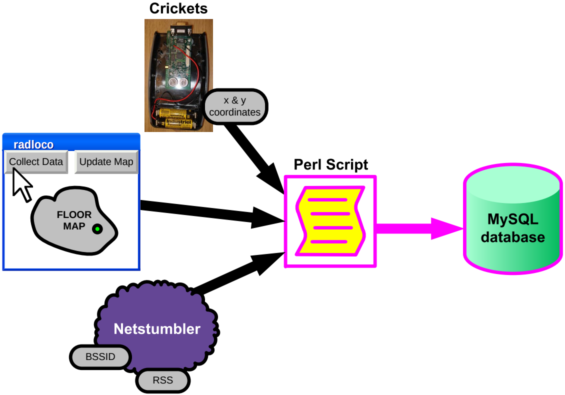
Software Setup



steps

crickets provide ground truth coordinates

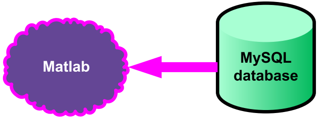
Software Setup



steps

RSS, BSSID and coordinates are saved to MySQL database

Software Setup



steps

data processing is performed in Matlab

Bayesian Estimation Algorithm - 1

Minimum Mean Square Estimate (MMSE)

The MMSE of the terminal location is

$$\hat{\theta}_{\mathrm{MMSE}} = \mathrm{E}\left[\theta|\boldsymbol{x}\right] = \int_S \theta f_\Theta(\theta|\boldsymbol{x})d\theta \tag{2}$$

The above equation can be expanded to

$$\hat{\theta}_{\mathrm{MMSE}} = \int_S \theta \frac{f_{\boldsymbol{X},\Theta}(\boldsymbol{x},\theta)}{f_{\boldsymbol{X}}(\boldsymbol{x})} d\theta = \frac{\int_S \theta f_{\boldsymbol{X},\Theta}(\boldsymbol{x},\theta)d\theta}{f_{\boldsymbol{X}}(\boldsymbol{x})} = \frac{\int_S \theta f_{\boldsymbol{X},\Theta}(\boldsymbol{x},\theta)d\theta}{\int_S f_{\boldsymbol{X},\Theta}(\boldsymbol{x},\theta)d\theta} \tag{3}$$

Bayesian Estimation Algorithm - 2

Minimum Mean Square Estimate (MMSE)

The joint approximate PDF is given by

$$\hat{f}_{\Theta,\boldsymbol{X}}(\theta, \boldsymbol{x}) = \frac{1}{N}(h_x)^{-L}(h_\theta)^{-2}\sum_{i=1}^{N} \mathrm{K}_{\boldsymbol{X}}\left(\frac{\boldsymbol{x}-\boldsymbol{X}_i}{h_x}\right)\mathrm{K}_{\Theta}\left(\frac{\boldsymbol{\theta}-\boldsymbol{\theta}_i}{h_\theta}\right) \tag{4}$$

with $\mathrm{K}(\cdot)$ being the Kernel functions for location and RSS measurements. The value L represents length of vector $\boldsymbol{x}$.

Kernel Function

For the kernel functions $\mathrm{K}(\cdot)$ we use the standard multivariate Gaussian distribution:

$$\mathrm{K}_{\boldsymbol{X}}(\boldsymbol{x}) = \left(\frac{1}{\sqrt{2\pi}}\right)^{L} \exp\left(-\frac{1}{2}(\boldsymbol{x}^T\boldsymbol{x})\right) \tag{5}$$

Bayesian Estimation Algorithm - 3

Joint approximate PDF

If we substitute the estimated PDF from Equation (4) into (3) and perform integration by substitution using $\boldsymbol{u} = \boldsymbol{\theta} - \boldsymbol{\theta_i}$, we can reduce:

$$\int \boldsymbol{\theta}\, \mathrm{K}_{\Theta}\left(\boldsymbol{\theta} - \boldsymbol{\theta_i}\right) d\boldsymbol{\theta} = \int \left(\boldsymbol{u} + \boldsymbol{\theta_i}\right) \mathrm{K}_{\boldsymbol{U}}(\boldsymbol{u}) d\boldsymbol{u} = \boldsymbol{\theta_i} \tag{6}$$

since the mean of the random variable $\boldsymbol{U}$ is:

$$\int \boldsymbol{u} K_{\boldsymbol{U}}(\boldsymbol{u}) d\boldsymbol{u} = 0$$

and

$$\int K_{\boldsymbol{U}} d\boldsymbol{u} = 1$$

Bayesian Estimation Algorithm - 4

Minimum Mean Square Estimate (MMSE)

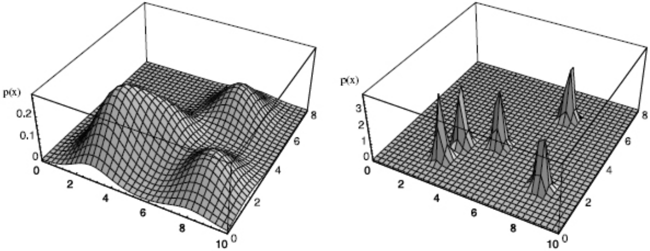
The resulting estimated location $\hat{\theta}$ is then a weighted average where the sum is taken across the weighted locations in the subset:

$$\hat{\theta} = \sum_{i=1}^{N} w_i \theta_i \tag{7}$$

with the weights w_i for each survey point i being defined as:

$$w_i = \frac{\mathrm{K}(\boldsymbol{x} - \boldsymbol{X}_i)}{\sum_{i=1}^{N} \mathrm{K}(\boldsymbol{x} - \boldsymbol{X}_i)} \tag{8}$$

Kernel Width



Kernel width

Small values of h_x indicate that the RSS vectors can change radically with short spatial displacements of the mobile device while larger values indicate that the RSS changes significantly only with large spatial displacements.

Kernel Width

Optimal Kernel Width

- two datasets are needed for training:
  1. survey set - dataset A
  2. validation set - dataset B.
- Each location in dataset B estimated using Kernel Estimator with survey dataset A, **while varying the parameter h_x**.
- The h_x that produces the minimum MSE is the optimal kernel width for the training dataset B.
- In theory, we need a training set of infinite size to determine optimal kernel. Therefore **optimal** means best kernel given our finite datasets.
- A third dataset C can be used for verification and is considered the test dataset. The set C is not used for training because it would extend the survey set.

Kernel Width

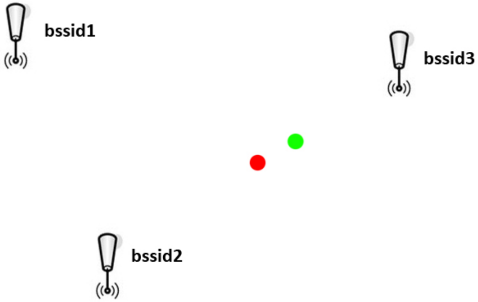
Cross-Validation

- collecting multiple datasets may be costly and time consuming: determine the optimal kernel width h_x for one dataset using a cross-validation approach.

$$MSE(h) = \sum_{i=1}^{N} \left[\boldsymbol{\theta}_i - \sum_{k=1,\neq i}^{N} w_k \boldsymbol{\theta}_k \right]^T \times \left[\boldsymbol{\theta}_i - \sum_{k=1,\neq i}^{N} w_k \boldsymbol{\theta}_k \right] \quad (9)$$

- remove a survey point from the survey set, then estimating the location of the survey point using the rest of the survey points, while varying h_x values.

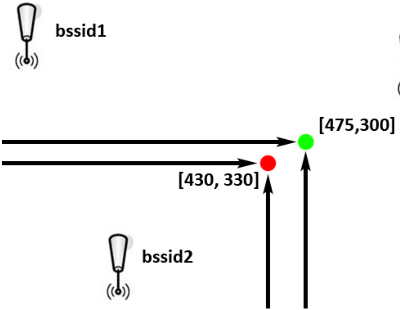
Error Calculation



Explanation

green dot = true location
red dot = estimated location

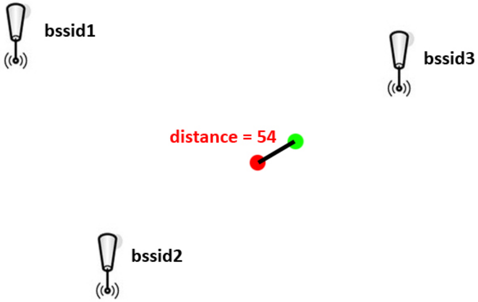
Error Calculation



Explanation

error distance = $\sqrt{(p_x - \hat{p}_x)^2 + (p_y - \hat{p}_y)^2)}$

Error Calculation



Explanation

error distance = $\sqrt{(p_x - \hat{p_x})^2 + (p_y - \hat{p_y})^2)}$